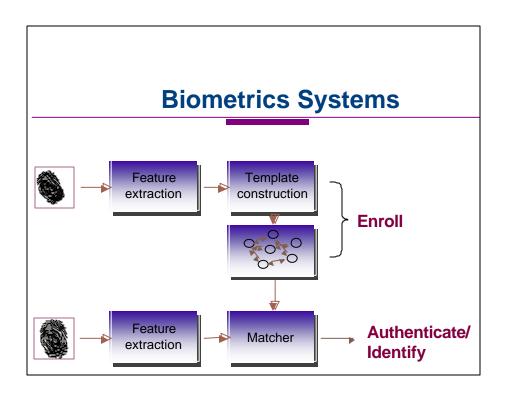
Accuracy Estimation of Biometrics Systems: *The Subsets Bootstrap*

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Outline

- Biometrics systems
- Performance accuracy
- Probability densities and distributions
- The match score distribution
- Confidence interval
- The Bootstrap
- The Subsets Bootstrap
- Experiments
- Conclusions



Pattern Recognition System

Two hypotheses:

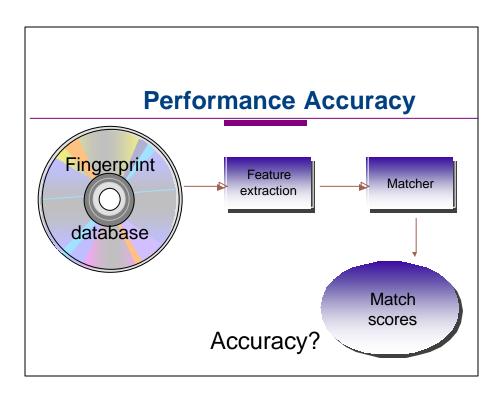
 H_o : $\boldsymbol{b} = \boldsymbol{b}'$, the claimed identity is correct

 $H_{\scriptscriptstyle 1}$: ${m b}
eq {m b}$ ', the claimed identity is not correct



A False Reject: Decide $H_{_{0}}$ while $H_{_{o}}$ is true

A False Accept: Decide $H_{\scriptscriptstyle 0}$ while $H_{\scriptscriptstyle 1}$ is true

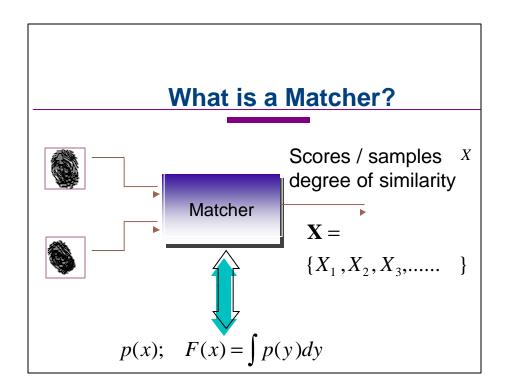


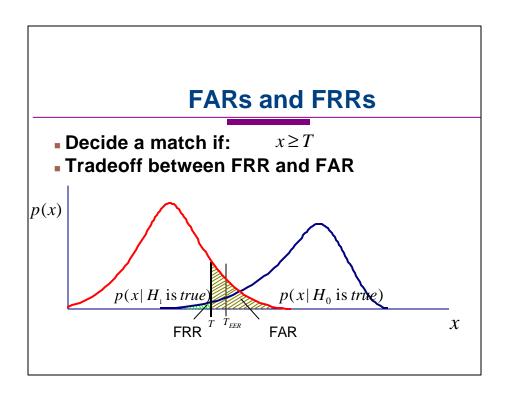
What is Accuracy?

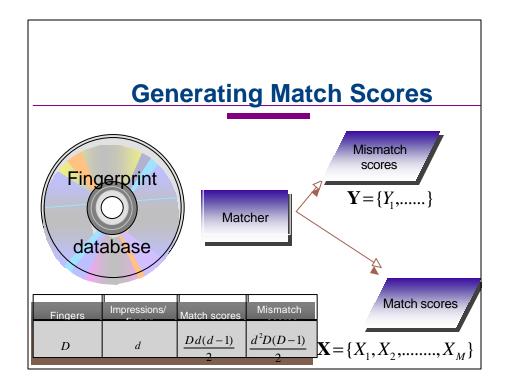
- False reject and false accept rates?
- Equal error rate?
- d-prime?
- **Receiver Operator Characteristic curve (ROC)?**
- All these are estimates....
- What is the significance of the estimator(s), i.e., confidence intervals?

Confidence Interval Estimation

- > Parametric
 - Assumes some parametric form of the underlying distribution
 - Binomial distribution of match scores; uses law of large numbers
- > Non-parametric
 - Bootstrap
- > Both methods assume i.i.d. samples
 - independently distributed
 - identically distributed



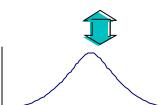


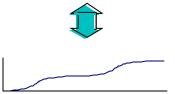


Probability Density

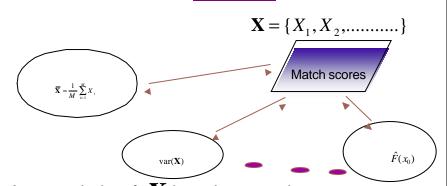
Of match scores $\mathbf{X} = \{X_1, X_2, \dots \}$

$$p(x|H_0 = true) \quad F(x) = \int_{-\infty}^{x} p(y|H_0 = true) \, dy$$





Computing Statistics



Any statistic of **X** is only an estimate: error measures are statistics, hence, random variables

Empirical Distribution

Match scores:

$$\mathbf{X} = \{X_1, X_2, ..., X_M\}$$

$$\hat{F}(x) = \frac{1}{M} \sum_{m=1}^{M} \mathbf{1}(X_m \le x) = \frac{1}{M} \#(X_m \le x)$$

$$\hat{F}(x)$$

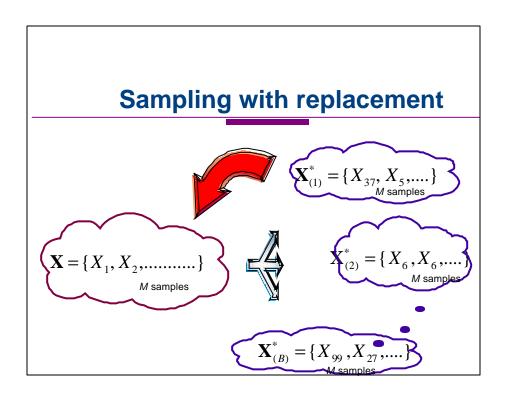
The Bootstrap

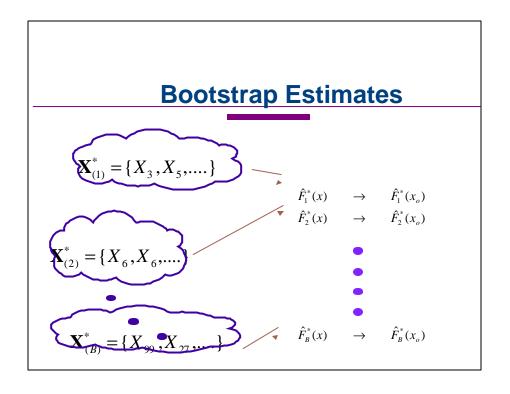
Assume $\hat{F}(x)$ is the true distribution F(x)

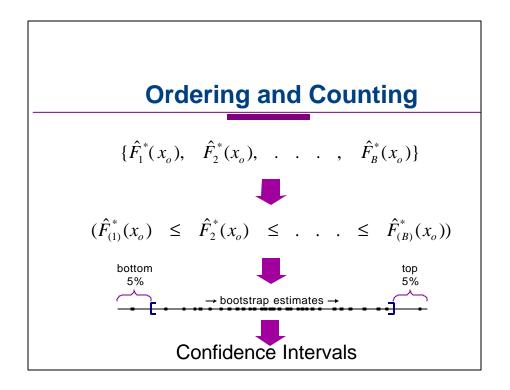
$$\hat{F}(x)$$

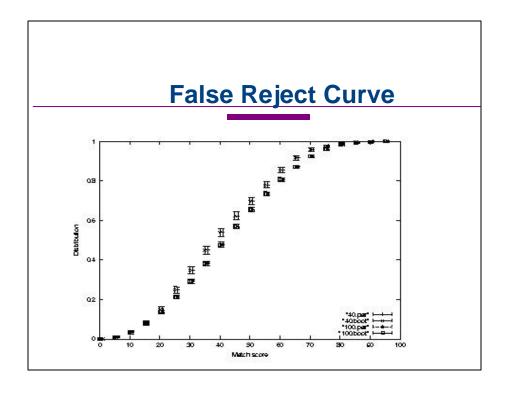
Sample X many (B) times, with replacement

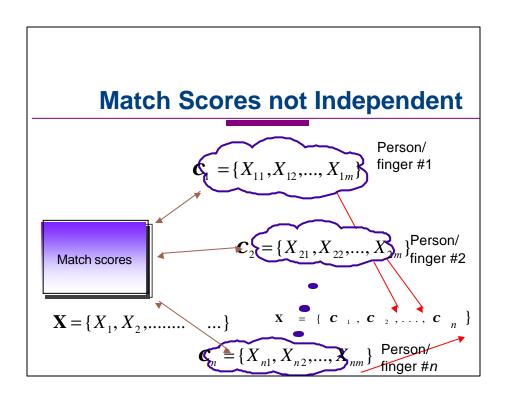
$$\mathbf{X}_{(1)}^*, \mathbf{X}_{(1)}^*,, \mathbf{X}_{(B)}^*$$

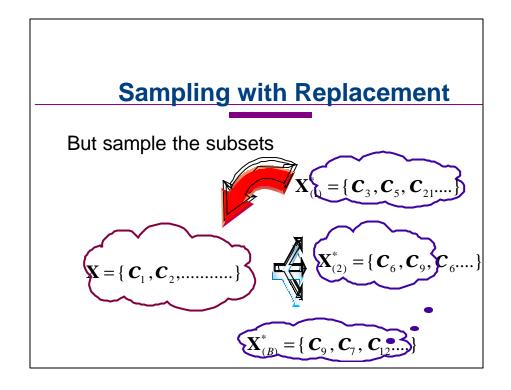


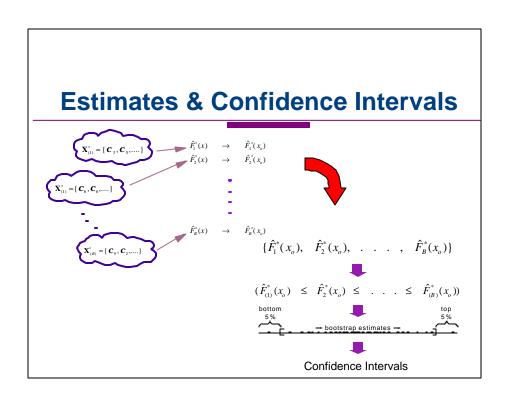


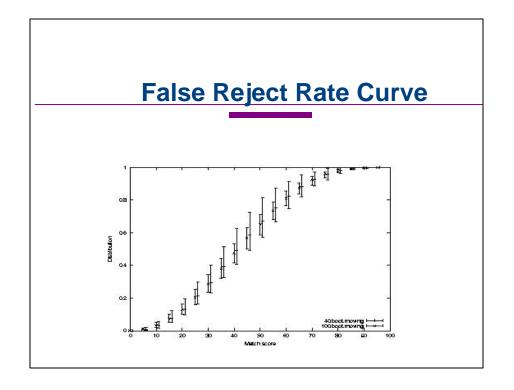












Replication of Dependence

$$\mathbf{X} = \{X_{1}, X_{2}, X_{3}, X_{4}, X_{5}, X_{1}, X_{2}, X_{3}, X_{4}, X_{15}, \dots, X_{M}\}$$

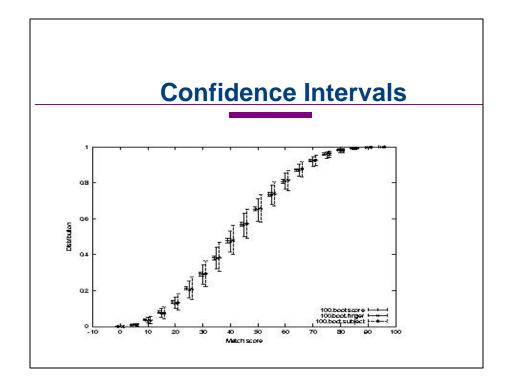
$$\mathbf{X}^{*} = \{X_{4}, X_{11}, X_{2}, X_{15}, X_{1}, X_{12}, X_{11}, X_{12}, X_{2}, X_{2}, X_{3}, X_{13}, X_{17}, X_{17}, \dots, X_{M}\}$$

$$\mathbf{X} = \{X_{1}^{a}, X_{1}^{b}, X_{1}^{c}, X_{1}^{d}, X_{2}^{a}, X_{2}^{b}, X_{2}^{c}, X_{2}^{d}, X_{3}^{a}, X_{3}^{b}, X_{3}^{c}, X_{3}^{d}, \dots, X_{m}^{a}, X_{m}^{b}, X_{m}^{c}, X_{m}^{d}\}$$

$$\mathbf{X} = \{\mathbf{C}_{1}, \mathbf{C}_{2}, \mathbf{C}_{3}, \dots, \mathbf{C}_{m}\}$$

$$\mathbf{X}^{*} = \{\mathbf{C}_{1}, \mathbf{C}_{1}, \mathbf{C}_{2}, \dots, \mathbf{C}_{9}\}$$

 $\mathbf{X}^{*} = \{X_{1}^{a}, X_{1}^{b}, X_{1}^{c}, X_{1}^{d}, X_{1}^{a}, X_{1}^{b}, X_{1}^{c}, X_{1}^{d}, X_{2}^{a}, X_{2}^{b}, X_{2}^{c}, X_{2}^{d}, ..., X_{9}^{a}, X_{9}^{b}, X_{9}^{c}, X_{9}^{d}\}$



Conclusions

- Many methods for computing confidence intervals underestimat the intervals
- Parametric methods underestimate the variance when data are dependent
- This is also true for the traditional Bootstrap
- For any biometrics, samples of the same person are not independent
- Bootstrap not so sensitive to "identical" assumption
- Introduced the <u>Subsets Bootstrap</u>: Divide the scores up into subsets that are independent
 - Sample the set of subsets with replacement to form bootstrap sets
 - Gives realistic estimates of confidence intervals

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http://www.research.ibm.com/people/r/ratha/autoid.html